Synoptic Weather Modeling and Estimates of the Exposure–Response Relationship between Daily Mortality and Particulate Air Pollution

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This study estimated the association between particulate air pollution and daily mortality in Utah Valley using the synoptic climatological approach to control for potential weather effects. This approach was compared with alternative weather modeling approaches. Although seasonality explained a significant amount of variability in mortality, other weather variables explained only a very small amount of additional variability in mortality. The synoptic climatological approach performed as well or slightly better than alternative approaches to controlling for weather. However, the estimated effect of particulate pollution on mortality was mostly unchanged or slightly larger when synoptic categories were used to control for weather. Furthermore, the shape of the estimated dose–response relationship was similar when alternative approaches to controlling for weather were used. The associations between particulate pollution and daily mortality were not significantly different from a linear exposure–response relationship that extends throughout the full observed range of pollution. *Key words*: air pollution, mortality, particle pollution, synoptic weather modeling, weather. *Environ Health Perspect* 104:414–420 (1996)

The effect of particulate air pollution on human health has been the subject of numerous evaluations. Studies have observed increased health risks associated with prolonged exposure to particulate air pollution (*1*). Two recent studies reported that long-term exposure to fine particulate air pollution was associated with increased risk of mortality—even after directly controlling for individual differences in age, gender, race, cigarette smoking, and other risk factors (*2,3*). Daily time–series studies have also observed associations between short-term (usually 1–5 days) changes in particulate air pollution and daily mortality as well as various measures of acute morbidity such as respiratory and cardiovascular hospital admissions, emergency department visits, exacerbation of asthma, increased respiratory symptoms, and lung function. The qualitative and quantitative consistency of this epidemiologic evidence has been summarized in several reviews (*4–8*).

Probably the most controversial finding of these studies is the association between daily mortality and particulate pollution. An important concern regarding the daily time–series mortality studies is the potential for confounding by weather variables. Regression models were statistically estimated to evaluate effects of pollution while simultaneously controlling for season and a limited number of weather variables—usually only temperature and humidity. Statistically significant associations with mortality were usually observed for both particulate pollution and weather variables. Temperature–mortality relationships were typically nonlinear with the largest weather effects at temperature extremes. Estimated exposure–response relationships between particulate pollution and mortality were usually monotonic and approximately linear, even at relatively low concentrations.

An alternative approach to control for weather and climate on human health implies that only one or two weather variables such as temperature and humidity may not be adequate to control fully for the effects of weather. It is possible that the selection of these two variables, and the use of subjective cutoff points to determine extreme weather days, might not be adequate to remove completely the confounding impact of weather in a particulate–mortality analysis. A "synoptic climatological approach" to model climate as a holistic unit composed of multiple meteorological elements has been proposed (*9–12*). This approach implies that organisms respond to the interaction of numerous meteorological elements which interact simultaneously, and typical "air masses," which represent frequently occurring meteorological complexes, can be identified for a locale in an automated fashion. Thus, potential weather thresholds and synergistic interactions between a variety of weather variables can be evaluated with a greater degree of precision.

The analysis reported in this paper is motivated by continued concerns that associations between daily mortality and particulate pollution may be due to residual confounding of weather, and by disagreements about the efficacy of various approaches to control for potential weather effects. The primary objective of this analysis is to use a synoptic climatological approach to control for weather effects in a well-defined daily time-series mortality data set and to answer three principal questions: 1) Does this synoptic approach do a better job of controlling for weather than previously used alternative approaches? 2) Is the size of the estimated pollution–mortality effect sensitive to alternative approaches to controlling for weather? and 3) Is the shape of the exposure–response relationship between particulate pollution and mortality affected by alternative approaches to controlling for weather?

Methods

Study Area

The bulk of Utah's population resides on a relatively narrow strip of land commonly referred to as the "Wasatch Front." This land area is approximately 10–15 miles wide from east to west and 80 miles long from north to south; it is bordered on the east by the Wasatch mountain range and on the west largely by the Great Salt Lake and Utah Lake. There are three distinct metropolitan areas on the Wasatch Front: the city of Ogden and surrounding communities to the north, Salt Lake City and surrounding communities located in the center, and several contiguous cities including Provo and Orem to the south. Because of its proximity with the Great Salt Lake, the part of the Wasatch Front that includes Salt Lake City is often referred to as "Salt Lake Valley." Because of its proximity with Utah Lake, the southern part of the Wasatch Front that includes the Provo/Orem metropolitan area is referred to as "Utah Valley." Although the entire Wasatch Front shares common weather patterns, emission sources of pollution differ across the three metropolitan areas resulting in somewhat different pollution levels and patterns.

The study area used in this analysis is Utah County, which includes Utah Valley,

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located at the southern end of the Wasatch Front. In 1990 the county had a population of about 265,000 of which approximately 188,000 resided in several contiguous cities (including Provo and Orem). Only approximately 6% of the area's adults smoke. Over the last several years, respirable particulate air pollution with an aerodynamic diameter ≤ 10 μm (PM_{10}) in Utah Valley has been associated with several health endpoints (*13*) including changes in lung function, respiratory symptoms, school absences, respiratory hospitalizations, and cardiopulmonary mortality.

During low-level temperature inversion episodes common to winter months, PM_{10} concentrations can become highly elevated due to local emissions being trapped in a stagnant air mass near the valley floor. A characteristic feature of the Utah Valley experience was the intermittent operation of the principal point source of particulate pollution, an integrated steel mill that was constructed during World War II. Due to a labor dispute and subsequent change in ownership, the mill was shut down for a 13-month period in 1986 and 1987. The closure resulted in a corresponding reduction in local particulate air pollution levels through an entire winter period. This natural experiment allows for more opportunity to separate particulate pollution effects from weather effects.

Another important aspect of the valley is that relatively low concentrations of sulfur dioxide (SO_2), ozone (O_3), and aerosol strong acidity reduces the potential of confounding by these other pollutants. Concentrations of SO_2 are so low that the state conducts only periodic monitoring which indicated that SO_2 levels average less than 0.01 ppm with a maximum 1-hr concentration less than 0.04 ppm. During hot summer afternoons in the valley ozone concentrations occasionally approach 0.12 ppm but, during winter months when particulate pollution levels are the highest, conditions necessary for substantial O_3 formation do not exist. Sampling of aerosol strong acidity conducted during the winter of 1989–1990 indicated that particulate acidity was extremely low and never exceeded the equivalence of 0.5 μg/m^3 H_2SO_4.

Data

Mortality data files for 1985 through 1989 were obtained from the Utah State Department of Health, Bureau of Vital Records and Health Statistics. Deaths from accidents (ICD9 ≥ 800) and deaths of residents outside of Utah County were excluded. Also, because PM_{10} data were unavailable, deaths prior to 7 April 1985 were excluded. Therefore, the full study period included 7 April 1985 through 31 December 1989. Mortality was also divided into three broad cause-of-death groups: 1) respiratory disease (ICD9 480-486, 490-496), 2) cardiovascular disease (ICD9 390-448), and 3) all other, excluding accidental deaths. The mortality count data are summarized along with several other key variables in Table 1.

Respirable particulate air pollution data were obtained from the Utah State Department of Health, Bureau of Air Quality. Monitoring was conducted in accordance with the Environmental Protection Agency's reference method for monitoring PM_{10}. Monitoring of PM_{10} data began at a site in Lindon in April 1985 and data were available for 83% of the days in the study period. Two additional PM_{10} monitoring sites were later established in Orem and Provo. Based on data from all three sites, average PM_{10} levels are somewhat uniform throughout the densely populated area of the valley and daily changes in PM_{10} levels at the three monitoring cites are highly correlated with each other ($r > 0.90$). In this analysis PM_{10} data from the Lindon site were used because this was the only site that monitored throughout the study period and because PM_{10} concentrations at all three sites closely tracked concentrations at the Lindon site.

Weather data were obtained from two sources. A limited number of weather variables, including daily low temperature and low relative humidity, were obtained from the Brigham Young University weather station. The more intensive weather data required to develop synoptic weather categories were obtained from the Salt Lake City International Airport first-order weather station (*14*). As air masses cover large contiguous areas, the entire Wasatch Front is within the same air mass type on any given day. The day-to-day passage of fronts and movement of pressure systems permits different air masses to intrude into the valley, though some may remain for a number of consecutive days.

Synoptic Weather Categories

An automated air mass-based synoptic climatological index was developed for the region from the Salt Lake City weather data to categorize each day into its particular synoptic weather category (SWC). The synoptic procedure used here, known as the temporal synoptic index (TSI), is designed to group days into particular air masses; thus these days possess similar and distinctive thermodynamic character (*15*). Grouping is accomplished by defining each day in terms of seven readily available meteorological elements, which include air temperature, dewpoint temperature, visibility, total cloud cover, sea-level air pressure, wind speed, and wind direction. These elements are measured four times daily (0100, 0700, 1300, 1900 hr local standard time), and the developed 28 variables represent the basis for categorization.

TSI uses nonrotated principal components analysis (PCA), a factor analysis technique that rewrites the original meteorological data matrix into a new set of components that are linearly independent and ordered by the amount of variance they explain. A detailed explanation of this procedure is given by Kalkstein et al. (*16*). Component loadings are then calculated, which express the correlation between the original 28 variables and the newly formed components. Each day is then expressed by its particular set of "component scores," which are weighted summed values whose magnitudes are dependent on the weather observation for each day and the principal component loading. Thus, days with similar meteorological conditions will tend to exhibit proximate component scores.

A hierarchical, agglomerative clustering procedure is then used to group those days with similar component scores into meteorologically homogeneous groups. This procedure, known as "average linkage clustering," is best-suited when the number of air mass categories to be developed is not predetermined (*17*). Grouping is based on a measure of similarity between pairs of objects (days); guidelines are provided to

Table 1. Summary of key variables in the Utah Valley daily time-series mortality study (April 1985–December 1989)

Variable	No. of days	Mean	SD	Minimum	Maximum
Daily mortality, all causes[a]	1736	2.7	1.7	0	12
Daily mortality, pulmonary	1736	0.3	0.5	0	3
Daily mortality, cardiovascular	1736	1.2	1.1	0	6
PM_{10}, concurrent day (μg/m^3)	1436	47	38	1	365
PM_{10}, 5-day lagged moving average (μg/m^3)	1706	47	34	11	297
Low temperature (°F)	1736	40	15	-20	72
Low relative humidity	1736	30	14	6	92

[a]Deaths from accidents (ICD9 ≥ 800) were excluded.

terminate clustering when dissimilar days are forced into the same group (*18*). Once the groups (air masses) have been determined, average values are calculated for the 28 meteorological variables for all days within each particular group. Weather map classification is also possible by reviewing maps for those days within a group, and describing general similarities. In addition, mean mortality and mean particulate concentration can be determined for each air mass.

Nineteen air mass types, or synoptic categories, were generated through the TSI (Table 2), and it is clear that they are rather distinctive. For example, based on their temperature regimes, types 101 through 105 are summer air masses, while types 300, 600, 1100, and 1200 occur mainly in winter. Not surprisingly, relative humidities are generally higher for the cool season air masses. Mean death counts vary among the groups, but are generally higher for the cool season air masses.

Table 2. Description and summary of synoptic categories

Synoptic weather categories	Days in study period	Mean death count	Mean PM_{10} (μg/m^3)	Mean low temperature	Mean high temperature	Mean low relative humidity
101	285	2.5	40	55	90	19
102	97	2.2	30	59	88	27
103	46	2.8	38	51	87	18
104	48	2.9	36	54	84	23
105	92	2.7	36	57	90	23
200	199	2.6	47	37	68	24
300	288	2.8	60	27	47	40
400	161	2.8	31	35	54	41
500	271	2.7	32	43	69	30
600	147	2.8	107	15	35	42
700	33	3.0	29	43	66	32
800	14	1.9	31	56	82	30
900	13	3.2	23	32	45	51
1000	22	3.1	48	55	87	21
1100	6	2.3	47	15	28	43
1200	6	4.2	145	-5	18	47
1300	2	2.0	58	6	18	39
1400	1	3.0	—	24	44	33
1500	1	5.0	—	42	55	54

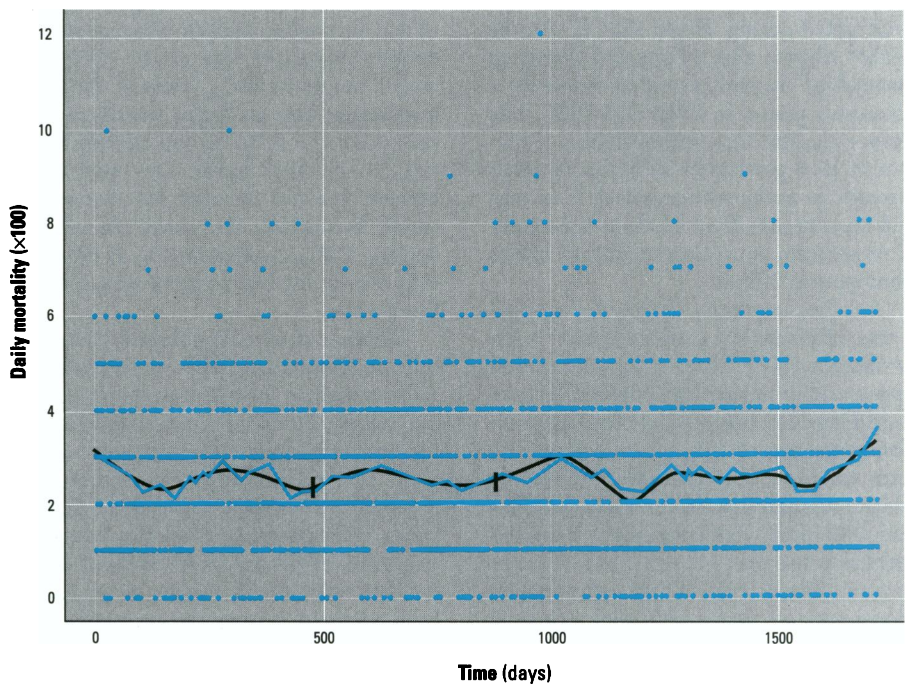

Figure 1. Daily mortality counts in Utah Valley plotted versus time. The dots represent the number of deaths on each of the 1736 days of the study period (April 1985–December 1989). The smoothed curves were fit using locally weighted regression smoothing with spans of 0.10 and 0.05. The two vertical bars on the smoothed curves indicate the date when the steel mill closed and the date when it reopened, respectively.

Statistical Analysis

For small populations, mortality is classically modeled as following a Poisson process which can generally be described as a process that generates independent and random occurrences across time or space (*19*). If time is divided into discrete periods such as 24-hr periods, or days, the daily death counts theoretically would be distributed as a Poisson distribution. Poissonian variation may account for most of the day-to-day variation in death counts, but the underlying mean of the process may be determined by pollution levels, season, weather, or other factors. Poisson regression attempts to model the temporal relationships between mean daily mortality and mortality risk factors while explicitly recognizing that most of the day-to-day variability is likely due to Poissonian variability.

In this analysis, we first estimated a series of standard parametric Poisson regression models (*20*). Different combinations of variables including pollution levels, indicator variables for seasons, quintile indicator variables for ranges of minimum temperatures and humidity, and indicator variables for the 19 synoptic categories were included as covariates in the models. The indicator variables for season could account for potential long-term time trend and seasonality because an independent indicator variable was created for each of the 20 seasons in the study period. Season one included April and May of 1985; season two, June, July, and August of 1985; seasons 3–19 included successive 3-month periods; and season 20 included December 1989. The indicator variables for seasons and the quintile of weather variables allowed for nonlinear, "stair-step" relationships to be estimated. The parametric Poisson models were estimated using the GENMOD procedure of SAS/STAT statistical software (*21*). Likelihood ratio tests were used to evaluate if the inclusion of seasonal and weather indicators significantly improved the models' ability to explain mortality (*22*).

Second, a series of nonparametric or generalized additive models (GAM) (*23*) was estimated. For the nonparametric Poisson models, pollution variables were included as linear variables in the models. However, rather than use indicator variables for years and months to account for time trends and seasonality, these models were fit using local regression smoothing of time. Similarly, rather than using indicator variables for different ranges of temperatures and humidity to account for nonlinear associations with these variables, some of these models were fit using local regression smoothing of temperature and humidity. These models were compared with models that used local regression smoothing of time but indicator variables for synoptic categories.

Models were estimated using subsets of the data restricted to cold periods (October–March) only and warmer periods (April–September) only. Based on early results (*24,25*) the pollution variable used in most of the models was a 5-day lagged moving average of PM_{10} (the mean of the nonmissing values of PM_{10} for the concurrent day and previous 4 days). However, this specific lag structure was further evaluated by estimating models with different lag structures for PM_{10}. The basic analysis controlled for weather using synoptic categories for the concurrent day, but a series of models using synoptic categories for prior days was estimated. Also, lagged moving average models for indicator variables for synoptic categories were estimated. In these models the binary (zero/one) indicator variable for a synoptic category on a given day was replaced by a moving average score. For example, the score for a synoptic category using a 4-day lagged moving average would equal 1, 0.75, 0.50, 0.25, or 0 if that category occurred during 4, 3, 2, 1, or 0 of the 4 days (the concurrent and previous 3 days).

Finally, to specifically evaluate exposure–response relationship between PM_{10} and mortality, models were fit using local regression smoothing of PM_{10}. The shape of the estimated exposure–response relationship was compared for models with varying degrees of control for season and weather, including models that use local regression smoothing to control for temperature and humidity versus models that controlled for weather using synoptic categories. To evaluate if the association between mortality and air pollution is significantly different from linear, models that allowed for nonlinear smooths of pollution levels were statistically compared with models where pollution was included as a simple linear term. These models were estimated using the generalized additive model (GAM) function and locally weighted regression smooths (LOESS) of S-PLUS statistical software (*26*).

Results

Daily death counts in Utah Valley plotted over the study period are presented in Figure 1. Underlying the Poissonian variability in daily death counts is evidence of seasonality. This seasonality is easily observed in the smoothed curves that are also plotted in this figure. The smoothest curve is fit to the data using locally weighted regression smoothing (LOESS), with a local span of 10% of the data, using a tricube weight function. This smooth is statistically significant ($p < 0.01$) indicating seasonal nonstationarity that must be accounted for in any analysis of the effects of air pollution. The more erratic curve is fit using a smaller span (5%). Intraseason variability is observed. Interestingly, the intraseason variability in mortality counts is much smaller during the period when the steel mill was closed and PM_{10} pollution episodes were substantially less severe.

Table 3 summarizes the regression results of the originally reported model (*24*), replicated results using an iteratively weighted and filtered least-squares Poisson regression model (*25*) and models 1–8 of our analysis. In model 1, mortality counts are only regressed on PM_{10}. Positive, statistically significant associations between total, pulmonary, and cardiovascular mortality and PM_{10} are observed. In models 2 and 3, the indicator variables for the 20 seasons in the study period to control for long-term time trends and seasonality and quintile indicator variables for temperature and relative humidity are added. The estimated PM_{10}–mortality effect was reduced somewhat. Likelihood ratio tests indicate that adding the seasonal indicator variables significantly ($p < 0.05$) improve how well the models explain changes in total and cardiovascular mortality, but that further adding the quintile indicator variables for temperature and relative humidity does not result in significant improvement. In model 4, when the quintile indicators for temperature and relative humidity are replaced with variables indicating synoptic categories, the PM_{10}–mortality effect size estimates actually increase again. Likelihood ratio tests indicate that adding the synoptic category variables result in significant ($p < 0.05$) improvement in how well the models explain changes in pulmonary and cardiovascular mortality. Although the overall ability to explain changes in mortality is not as good as model 4, nearly identical PM_{10}–mortality associations are observed in model 5, when

Table 3. Comparison of PM_{10} coefficients (×100) and standard errors for various Poisson regression models

Model	Model description	Mortality counts (SE)		
		Total	Pulmonary	Cardiovascular
Base I	Original model, Pope et al., 1992 (*24*)	0.147 (0.031)	0.361 (0.149)	0.179 (0.072)
Base II	Replicated model, Samet et al., 1995 (*25*)	0.160 (0.051)	0.390 (0.150)	0.180 (0.072)
Parametric models				
1	5-Day lagged moving average of PM_{10}	0.143 (0.041)	0.340 (0.118)	0.219 (0.058)
2	5-Day lagged moving average of PM_{10}; indicator variables for 20 seasons	0.113 (0.056)	0.249 (0.166)	0.156 (0.080)
3	5-Day lagged moving average of PM_{10}; indicator variables for 20 seasons; quintile indicator variables for temperature and relative humidity	0.120 (0.058)	0.280 (0.172)	0.147 (0.083)
4	5-Day lagged moving average of PM_{10}; indicator variables for 20 seasons; indicator variables for 19 synoptic weather categories	0.131 (0.058)	0.312 (0.171)	0.173 (0.083)
5	5-Day lagged moving average of PM_{10}; linear time-trend variable; Indicator variables for 19 synoptic weather categories	0.131 (0.047)	0.336 (0.139)	0.191 (0.067)
Nonparametric models				
6	5-Day lagged moving average of PM_{10}; LOESS smooth of time (span = 0.10)	0.114 (0.041)	0.247 (0.120)	0.164 (0.059)
7	5-Day lagged moving average of PM_{10}; LOESS smooths of time (span = 0.1), temperature (span = 0.5) and relative humidity (span = 0.5)	0.149 (0.048)	0.399 (0.141)	0.147 (0.069)
8	5-Day lagged moving average of PM_{10}; LOESS smooth of time (span = 0.10); indicator variables for 19 synoptic weather categories	0.132 (0.046)	0.307 (0.138)	0.188 (0.067)

LOESS, locally weighted regression smoothing.

the synoptic categories are used to control for seasonality and other weather changes.

Similar results are observed with nonparametric models. In model 6, a nonparametric smooth of time is included to control for long-term time trend and seasonality. Statistically significant ($p < 0.05$) seasonal nonlinearity is observed for total and cardiovascular mortality. The estimated PM_{10}–mortality effect is nearly identical to that estimated from model 2. In models 7 and 8 weather is controlled for by either nonparametric smooths of temperature and relative humidity or synoptic category indicators. The estimated PM_{10}–mortality effects are similar to those estimated in the comparable parametric models (models 3, 4, and 5). Furthermore, similar estimates of PM_{10}–mortality effects are obtained when weather is controlled for using synoptic categories.

In Table 4, PM_{10}–mortality effect estimates are presented for models that control for temperature and humidity and models that control for synoptic categories after separating the data by cold and warm periods (models 9–12). For both periods, the PM_{10}–mortality association is positive, but because most of the variability in PM_{10} pollution in Utah Valley occurs during winter months, the association is only statistically significant for the cold periods. In Table 4, PM_{10}–mortality effect estimates are presented from models that use different lagged times for PM_{10} (models 13–17) and for weather (models 18–23). Lagged averaging times of 1–6 days are included in the models. Although the PM_{10}–mortality association is positive for all lag times, the 5-day lagged moving average of PM_{10} fit the data best.

PM_{10}–mortality effect estimates from models using different lag times for synoptic categories are estimated. Previous studies that evaluated mortality and synoptic categories have indicated that mortality is associated primarily with concurrent day weather or weather on the preceding one, two, or three days (*12*). The estimated PM_{10}–mortality association is not highly affected by the choice of lag structure used to control for synoptic categories (compare results of models 18–23 in Table 4 with model 8 in Table 3). The standard errors of the PM_{10}–mortality coefficients are consistently smaller when weather is controlled for by using concurrent day synoptic categories versus alternative lag times.

The PM_{10}–mortality exposure–response relationship is determined more flexibly by fitting four nonparametric models after replacing the linear PM_{10} term with a locally weighted regression smooth of PM_{10}. The estimated exposure–response relationships from these models are presented in Figure 2. Plot A corresponds to the exposure–response from a model where mortality counts are regressed only on the nonparametric smooth of PM_{10}. Plot B corresponds to a model that adds a nonparametric smooth of time to control for long-term time trend and seasonality. Plot C corresponds to a model that includes the nonparametric smooth of time and controlled for weather using smooths of temperature and relative humidity. Plot D corresponds to a model that replaces the nonparametric smooths of temperature and relative humidity with the indicator variables for the 19 synoptic categories.

Table 4. Comparison of PM_{10} coefficients (×100) and standard errors for various Poisson regression models restricted to warm and cold periods and for different lag lengths

		Mortality counts (SE)		
Model	Model description	Total	Pulmonary	Cardiovascular
Restriction to cold and warm periods				
9	Model 7, cold periods (Oct–March)	0.136 (0.054)	0.271 (0.158)	0.120 (0.078)
10	Model 7, warm periods (April–Sept)	0.212 (0.195)	0.849 (0.645)	0.103 (0.294)
11	Model 8, cold periods (Oct–March)	0.114 (0.049)	0.226 (0.145)	0.145 (0.071)
12	Model 8, warm periods (April–Sept)	0.175 (0.187)	0.664 (0.620)	0.047 (0.279)
Different lag times for PM_{10}				
13	Model 8 but concurrent-day PM_{10}	0.045 (0.050)	0.040 (0.152)	0.051 (0.073)
14	Model 8 but 2-day lagged moving average of PM_{10}	0.068 (0.047)	0.109 (0.144)	0.076 (0.068)
15	Model 8 but 3-day lagged moving average of PM_{10}	0.088 (0.047)	0.139 (0.143)	0.099 (0.068)
16	Model 8 but 4-day lagged moving average of PM_{10}	0.124 (0.046)	0.273 (0.138)	0.166 (0.067)
17	Model 8 but 6-day lagged moving average of PM_{10}	0.115 (0.048)	0.255 (0.144)	0.182 (0.068)
Different lag times for SWC				
18	Model 8 but SWC of 1 day prior	0.151 (0.048)	0.387 (0.143)	0.203 (0.069)
19	Model 8 but SWC of 2 days prior	0.098 (0.051)	0.280 (0.152)	0.156 (0.074)
20	Model 8 but SWC of 3 days prior	0.107 (0.054)	0.243 (0.162)	0.175 (0.077)
21	Model 8 but 2-day lagged moving average of SWC	0.154 (0.048)	0.373 (0.145)	0.209 (0.070)
22	Model 8 but 3-day lagged moving average of SWC	0.141 (0.052)	0.380 (0.153)	0.196 (0.074)
23	Model 8 but 4-day lagged moving average of SWC	0.133 (0.056)	0.359 (0.165)	0.188 (0.080)

SWC, synoptic weather categories.

The observed PM_{10}–mortality associations presented in Figure 2 are similar to those estimated in models that included PM_{10} as a linear term (models 1, 6, 7, and 8). Also, as can be observed in Figure 2, neither the size of the association, nor the shape of the dose–response relationship is highly affected by alternative approaches to controlling for weather, including the use of synoptic categories. For all of the models presented in Figure 2, a statistically significant positive association between PM_{10} and mortality is observed. However, no statistical inferences can be made about the small local nonlinearities that can be observed. Chi-square tests of nonlinearity indicate that the observed associations between mortality and particulate pollution are not significantly different from linear ($p > 0.50$).

Discussion

A primary objective of this analysis is to employ synoptic categorization to control for potential weather effects within the Utah Valley daily time–series mortality data. Three questions are posed. First, does the synoptic categorization do a better job of controlling for weather than previously used alternative approaches? Yes, there is slight improvement, but it should be noted that in the Utah Valley data, weather variables explain only a very small amount of additional variability in mortality. Seasonality explains a more significant amount of variability in mortality. Based on the parametric models and likelihood ratio tests, adding the seasonal indicator

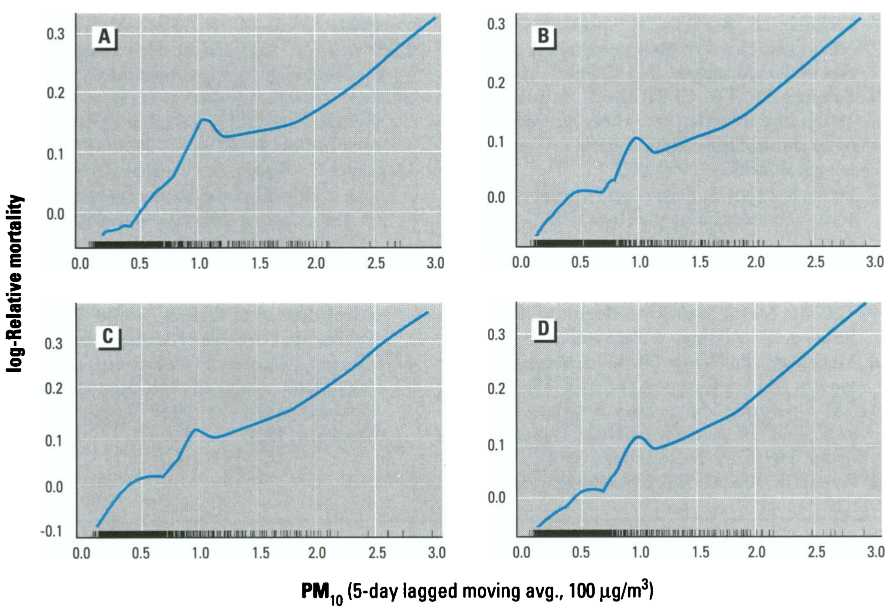

Figure 2. Log-relative mortality rates plotted versus PM_{10}. Data are for Utah Valley, April 1985–December 1989. Curves were estimated using generalized additive models with locally weighted regression smoothing of PM_{10} (span = 0.5). (A) Exposure response from a model where mortality counts were regressed only on the nonparametric smooth of PM_{10}; (B) model that adds a nonparametric smooth of time to control for long-term time trend and seasonality; (C) model that includes the nonparametric smooth of time and controlled for weather using smooths of temperature and relative humidity; (D) model that replaces the nonparametric smooths of temperature and relative humidity with the indicator variables for the 19 synoptic categories.

variables significantly improve how well the models explain changes in total and cardiovascular mortality. Adding additional variables for only temperature and relative humidity does not result in significant improvement, but adding the synoptic category variables does result in a significant ($p < 0.05$) improvement in how well the models explain changes in pulmonary and cardiovascular mortality. These results may be different for other cities, such as Philadelphia, where weather has a larger effect on the variability of daily mortality (*12,27*).

Second, is the size of the estimated pollution–mortality association sensitive to alternative approaches to controlling for weather? The size of the association is remarkably consistent across a wide range of models, and consistent with the results originally reported. The estimated PM_{10}–mortality effect is mostly unchanged by the use of the synoptic categories versus the alternative approaches that have been used in most previous studies. In fact, controlling for weather using synoptic categories results in slightly higher PM_{10}–mortality effect estimates. These results do not suggest that there are no effects of weather. They do suggest, however, that there is an association between PM_{10} and mortality that is independent of weather effects.

Third, is the shape of the exposure–response relationship between particulate pollution and mortality affected by alternative approaches to controlling for weather? Nonparametic modeling of the relationship between PM_{10} and mortality is conducted with and without control of weather. Both the size of the association and the shape of the estimated dose–response relationship are similar when alternative approaches to controlling for weather, including the use of synoptic categories, are used. The results consistently observe positive, statistically significant, associations between PM_{10} and daily mortality. These associations are not significantly different from a linear exposure–response relationship that extends throughout the full observed range of particulate pollution.

One important limitation of this study is that the relative importance of weather observed in this study may not be generalizable to other areas. It is possible that in other cities, weather may be more important and potentially a more significant confounder of the PM_{10}–mortality estimates. In Utah Valley there may be less oppressive or offensive weather than some other places. While the valley does experience some hot summer weather, the valley does not experience extreme hot and humid weather conditions that occur in some other cities. Also, adequate housing in the valley likely mitigates exposure to extreme weather conditions and pollution. Another limitation of this study is lack of statistical power to evaluate weather and pollution effects separately by season. Synoptic categorization can be developed on a season-by-season basis, resulting in a more weather-intensive analysis. Finally, it is important to replicate this analysis in other cities with different population characteristics and weather patterns.

Synoptic categorization provides a quality means to control for weather in mortality–pollution analyses. The procedure is based on the premise that the population responds to weather situations, rather than individual weather variables, a widely accepted notion in bioclimatological research. Thus, we think that synoptic categorization can be utilized successfully in similar studies for numerous locations where the more than 300 first-order weather stations in the U.S. are adjacent.

This analysis of the Utah Valley mortality data using synoptic categorization to control for weather continues to suggest an intriguing, statistically robust relationship between mortality and particulate air pollution. This study with various morbidity studies in Utah Valley, provide substantial evidence that respirable particulate pollution, some constituent of this pollution, or some pollutant that is closely associated with respirable particulate pollution, is an important risk factor for respiratory disease and cardiopulmonary mortality.

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